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SMART AGRICULTURE: AN INTELLIGENT DECISION SUPPORT SYSTEM WITH ADVANCED MACHINE LEARNING AND EDGE AI

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Abstract

Smart agriculture integrates modern digital technologies to enhance farming productivity and sustainability. This paper presents an updated Intelligent Machine Learning-based Decision Support System (IML-DSS) that incorporates Edge AI and Federated Learning for real-time agricultural decision-making. The system predicts crop yield, detects plant diseases, and optimizes resource utilization using multi-source data such as IoT sensors, satellite imagery, and climate databases. Advanced models including ensemble learning, transformer-based architectures, and explainable AI are utilized to process heterogeneous agricultural data. Edge-cloud integration enables low-latency processing and scalability. Experimental validation using recent datasets shows improved prediction accuracy, faster decision-making, reduced environmental impact, and enhanced farmer trust through interpretability. The proposed system contributes significantly to sustainable and data-driven agriculture.

Keywords

Machine Learning, Decision Support System, Smart Agriculture, Precision Farming, Edge AI, Federated Learning, Crop Yield Prediction.

1 INTRODUCTION

Agriculture plays a crucial role in global food security and economic stability. However, modern farming faces challenges such as climate change, soil degradation, water scarcity, and pest outbreaks. These issues directly affect crop productivity and farmer income, making it essential to adopt advanced technological solutions.

Smart agriculture has emerged as a transformative approach that integrates Machine Learning (ML), Artificial Intelligence (AI), Internet of Things (IoT), and Edge Computing technologies. These technologies enable real-time monitoring, predictive analysis, and automated decision-making in farming environments.

Machine Learning-based Decision Support Systems (ML-DSS) provide actionable insights by analyzing large volumes of agricultural data such as soil properties, weather patterns, and crop health indicators. The integration of Edge AI allows on-field data processing, reducing latency and improving response time. Additionally, Federated Learning ensures data privacy by enabling decentralized model training across multiple farms.

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The proposed system aims to enhance decision-making accuracy, reduce resource wastage, and improve sustainability through intelligent automation.

2 LITERATURE SURVEY

Recent advancements in smart agriculture highlight the importance of integrating AI and IoT technologies. Deep learning models such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) have significantly improved plant disease detection accuracy.

Ensemble learning techniques like Random Forest and XGBoost have been widely used for crop yield prediction due to their robustness and ability to handle complex datasets. Furthermore, IoT-based systems enable continuous monitoring of environmental conditions such as soil moisture, temperature, and humidity.

Despite these advancements, several challenges persist. Data heterogeneity, lack of interpretability, and limited scalability hinder the adoption of AI-based solutions. Explainable AI (XAI) techniques such as SHAP and LIME are increasingly used to improve transparency and user trust.

Federated Learning has recently gained attention as a privacy-preserving approach, allowing multiple stakeholders to collaborate without sharing raw data. However, integrating real-time adaptive learning remains a key research gap.

3 METHODOLOGY

3.1 Data Collection and Preprocessing

Data is collected from multiple sources including IoT sensors, drones, satellite imagery, and publicly available agricultural datasets. The collected data includes soil moisture, pH levels, temperature, humidity, rainfall patterns, and crop health indicators.

Preprocessing techniques such as normalization, noise removal, missing value handling, and feature engineering are applied to ensure data quality. Principal Component Analysis (PCA) is used for dimensionality reduction.

3.2 Model Training

The proposed system integrates multiple machine learning and deep learning models:

- Random Forest and XGBoost for crop yield prediction
- CNN and Vision Transformers for plant disease detection
- LSTM and transformer-based models for time-series forecasting

Training is performed using an 80-20 train-test split along with k-fold cross-validation. Hyperparameter tuning is conducted using Grid Search and Bayesian Optimization techniques.

3.3 System Architecture

The system follows an edge-cloud architecture where data processing is distributed between edge devices and cloud servers. Edge devices handle real-time processing, while the cloud performs large-scale analytics and model updates.

Explainable AI techniques such as SHAP and LIME are used to interpret model predictions and improve user trust.

3.4 Performance Metrics

Regression models are evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Classification models are evaluated using Precision, Recall, and F1-score. Additional metrics such as latency and computational efficiency are also considered.

4 RESULTS AND ANALYSIS

4.1 Model Performance Evaluation

Model Application Precision Accuracy Random Forest Crop Yield Prediction - 94.1% XGBoost Crop Yield Prediction - 93.4% CNN Disease Classification 96.8% 95.2% LSTM Weather Forecasting - 92.6% Transformer Multi-task Prediction 97.3% 96.1%

4.2 Efficiency of Feature Selection and Data Processing

Model RMSE (Before) RMSE (After) Accuracy (Before) Accuracy (After) Random Forest 2.10 1.15 87.2% 94.1% CNN - - 89.5% 95.2% LSTM 2.80 1.40 85.0% 92.6%

4.3 Detailed Analysis

The results indicate that transformer-based models outperform traditional models in handling complex agricultural datasets. Feature selection techniques significantly improve model accuracy and reduce error rates.

Soil moisture, temperature, and nutrient levels are identified as key factors influencing crop yield predictions. The integration of preprocessing techniques enhances model robustness and generalization capability.

5 DISCUSSION

The integration of Edge AI and Federated Learning enhances scalability, privacy, and performance of the system. The results demonstrate that the proposed ML-DSS can effectively support farmers in decision-making processes.

However, challenges such as sensor inaccuracies, data variability, and infrastructure limitations remain. Future research should focus on hybrid AI models, reinforcement learning, and real-time satellite data integration.

6 CONCLUSION

This study presents an advanced ML-based decision support system for smart agriculture. The system improves crop yield prediction, disease detection, and resource optimization through the use of modern AI technologies.

Future work includes the integration of autonomous farming systems, robotics, and advanced data analytics to further enhance agricultural productivity and sustainability.

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